# On using EEG signals for emotion modeling and biometry

Arevalillo-Herráez, Miguel; Chicote-Huete, Guillermo; Ferri, Francesc J.; Ayesh, Aladdin; Boticario, Jesús G.; Katsigiannis, Stamos; Ramzan, Naeem; Arnau González, Pablo

*Published in:*
ESM '2019 Conference Proceedings

Published: 15/10/2019

*Document Version*
Peer reviewed version

# ON USING EEG SIGNALS FOR EMOTION MODELING AND BIOMETRICS

Miguel Arevalillo-Herráez, Guillermo Chicote-Huete, Francesc J. Ferri
Departament d'Informàtica. Universitat de València. Valencia, Spain
{miguel.arevalillo,guillermo.chicote,francesc.ferri}@uv.es

Aladdin Ayesh
Faculty of Technology. De Montfort University
Leicester, United Kingdom
aayesh@dmu.ac.uk

Jesús G. Boticario
Departamento de Inteligencia Artificial. UNED.
Madrid, Spain
jgb@dia.uned.es

Stamos Katsigiannis, Naeem Ramzan
School of Computing. University of the West of Scotland. Paisley, United Kingdom
{stamos.katsigiannis,naeem.ramzan}@uws.ac.uk

Pablo Arnau-González
CECOTEC Innovaciones, S.L
pablo.arnau@cecotec.es

**KEYWORDS**
EEG, Affect, Biometrics, Emotion modeling

**ABSTRACT**

A number of previous works have adopted a subject independent approach for recognizing emotions from Electroencephalography (EEG) signals, and attempted to build a global model by treating data from different subjects as if they belong to the same individual. In this paper we visually explore the data provided in four different standard datasets when using Power Spectral Density features, and show that the subject-dependent component in the EEG signal is far stronger than the emotion-related component. In addition, the session-dependency that is also found discourages the application of this type of features from EEG signals in a biometric context.

## INTRODUCTION

The existing relation between emotions and electrical activities of the brain (Soleymani et al. 2014) has motivated an extensive research on detecting emotions from electroencephalogram (EEG) signals, sometimes in combination with other sources of information (Lu et al. 2015, Koelstra et al. 2012, Soleymani et al. 2012a). In this context, we can clearly differentiate between two distinct approaches. On the one hand, subject-dependent methods (Sohaib et al. 2013, Salmeron-Majadas et al. 2015, Ayesh et al. 2016) create a model per individual, using training information that only refers to that person. On the other hand, subject-independent techniques (Wang et al. 2014, Hadjidimitriou et al. 2015, Liu et al. 2010) ignore specific subject traits, and train a single global model that aims to be valid for all users. The advantage of the latter strives on the fact that more training data becomes easily available due to combining data from all individuals in the dataset. It also means that no previous information about a specific subject is required to start the prediction task.

In this paper, we analyse the suitability of these two approaches for emotion detection from EEG signals when using Power Spectral Density (PSD) features. To this end, we use t-Distributed Stochastic Neighbor Embedding (t-SNE) (Maaten and Hinton 2008), a dimensionality reduction method which is specially suited for the visualization of high-dimensional datasets. As a first contribution, a visual exploration of the data reveals that samples from the same individual are naturally grouped in clusters, and suggests that the subject-related component of the signal has a relatively higher importance than the emotion-related component. Such observation reinforces the arguments provided in Ayesh et al. (2014), regarding the need to take into consideration a person individuality at expressing emotions. As a second contribution, and despite that this particular layout seems to support the suitability of EEG signals for biometric applications, we discover a strong dependency from the session that also hinders practical applications in this context. As a natural consequence, this opens the door to mixed or multi-task approaches in which emotion, identity and session jointly contribute to uncover hidden patterns in the data.

## DATA ANALYSIS

### Datasets

The growing interest in affect recognition from EEG signals has motivated the development of dedicated pub-

| Database | Number of participants | Number of videos | Video content | Video duration | Recording device | Number of channels | Sampling frequency | Number of sessions |
|---|---|---|---|---|---|---|---|---|
| DEAP | 32 | 40 | Music videos | 60 s | Biosemi Active II | 32 | 512 Hz (downsampled to 256 Hz) | 1 |
| MANHOB-HCI | 27 | 20 | Excerpts from movies | 34.9-117 s (avg=81s) | Biosemi Active II | 32 | 512 Hz (downsampled to 256 Hz) | 1 |
| DREAMER | 23 | 18 | Music videos | 65-393 s (avg=199s) | Emotive EPOC | 14 | 128 Hz | 1 |
| SEED | 15 | 15 | Excerpts from movies | 240 s | ESI NeuroScan | 62 (32 used) | 1000 Hz (downsampled to 200 Hz) | 3 |

Table 1: Summary of characteristics for the databases in the study

lic datasets. In between them, we find DEAP (Koelstra et al. 2012), MAHNOB-HCI (Soleymani et al. 2012b), DREAMER (Katsigiannis and Ramzan 2017), and SEED (Duan et al. 2013, Zheng and Lu 2015). These databases are composed of EEG recordings from subjects that were exposed to a series of video stimuli aimed at eliciting specific emotions. They all use Russell's two dimensional bipolar emotional model to label and represent emotions. The two dimensions are valence (positive or negative feeling) and activation/arousal (level of excitement) (Russell 1979), which are justified to account for the major proportion of variance in affect scales. In DEAP, MAHNOB-HCI and DREAMER, affective labels for valence and arousal were self-reported by the user using self-assessment manikins (SAM) (Morris 1995). As in previous works by other authors (Arnau-González et al. 2017, Koelstra et al. 2012, Liu et al. 2015, Petrantonakis and Hadjileontiadis 2010), the reported value was discretized into positive/negative using 5 (out of 10) as the threshold value. In SEED, recordings were instead annotated according to the expected emotional response, using three possible discrete values for valence: negative, neutral and positive.

Out of the four datasets described above, the only one that considers the concept of a session is SEED. In SEED, the experimental setting was repeated three times across different dates, recording the data for each session independently. A summary of the characteristics of the four datasets we have used in the paper is provided in Table 1.

### Features

PSD features have extensively been used for identifying emotions from EEG signals (Arnau-González et al. 2017, Katsigiannis and Ramzan 2017, Soleymani et al. 2012b, Koelstra et al. 2012). We computed the PSD in each of the available channels, discarding the information from the channels in SEED that were not available in DEAP and MANHOB. For consistency reasons and to ease the future comparison of results, this was done as in the original publications (Koelstra et al. 2012, Soleymani et al. 2012a, Zheng and Lu 2015), downsampling the signals to 128 Hz in the case of MANHOB, and using Welch's method with a Hamming window of 1 *sec*, with 50% overlapping. The spectral power was averaged over the $\theta$ (4-8 Hz), $\tilde{\alpha}$ (8-10 Hz), $\alpha$ (8-12 Hz), $\beta$ (12-30 Hz), and $\gamma$ (30+ Hz) bands for all channels or electrodes. In addition, the difference between the spectral power of all the symmetrical pairs of electrodes on the right and left hemisphere in the same bands was also computed in order to measure the possible asymmetry in the brain activities due to emotional stimuli. This yielded a vector of 230 features per recording in DEAP, MANHOB and SEED (32 electrodes $\times$ 5 bands + 14 pairs $\times$ 5 bands); and 105 in DREAMER (14 electrodes $\times$ 5 bands + 7 pairs $\times$ 5 bands).

## Dimensionality Reduction Experimentation

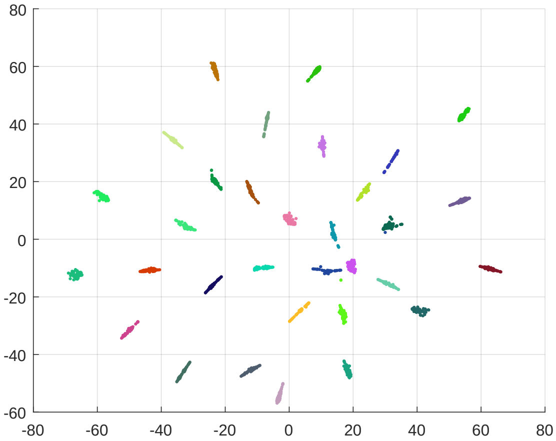
### Experimental setting

t-Distributed Stochastic Neighbor Embedding (t-SNE) (Maaten and Hinton 2008) is a technique for dimensionality reduction that is particularly well suited for the visualization of high-dimensional datasets. We have applied this method to EEG recordings from different individuals so as to reduce the dimensionality of these datasets into a two dimensional (2-D) space. In order to ensure consistency of the results, experiments have been repeated across the different databases described above.

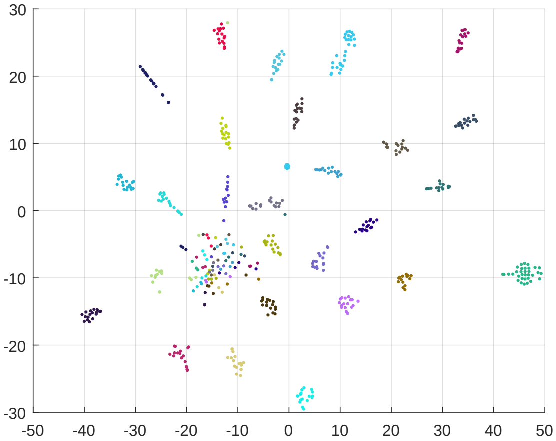
### Results and discussion

Figure 1 shows a 2-D representation of the data recordings stored in the DEAP, MANHOB and DREAMER datasets. The same kind of data for a representative session in SEED is shown in Figure 2.

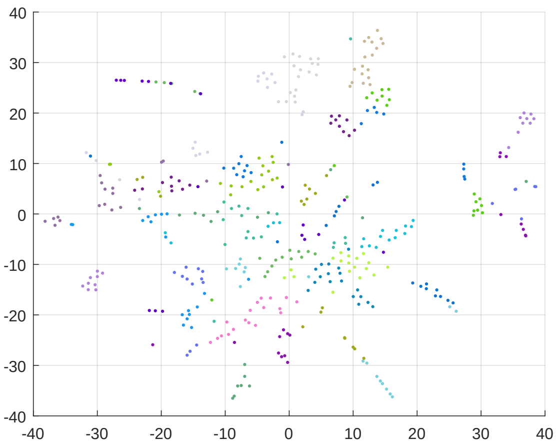
In all these plots, we have used the same color to represent recordings that belong to a same subject. This allows one to easily observe that EEG recordings are naturally clustered according to the subject they are associated with. This clustered structure is more ob-




(a)




(b)




(c)

Figure 1: Dimensionality reduction by t-SNE in (a) DEAP, (b) MANHOB and (c) DREAMER. EEG recordings from the same subject are plotted using the same color.

vious in DEAP and MANHOB, but still noticeable in DREAMER and SEED.

In all cases, samples (recordings) that belong to a same

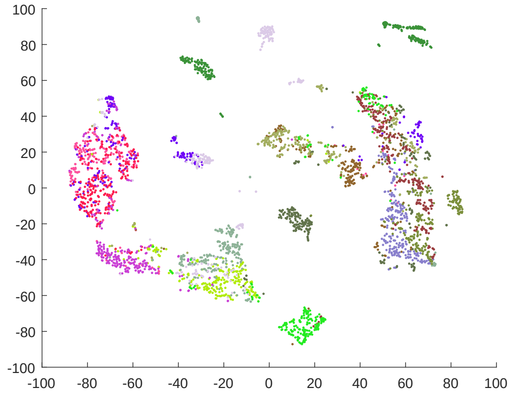
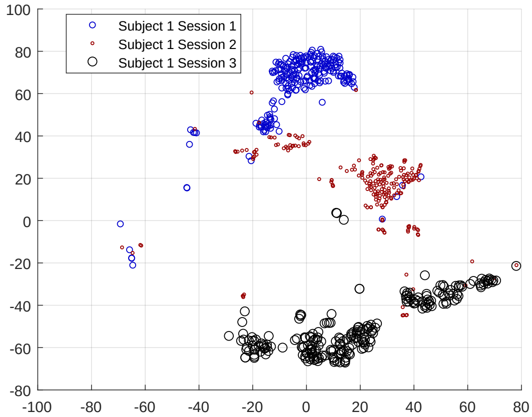



Figure 2: Dimensionality reduction by t-SNE for a session in SEED. EEG recordings from the same subject are plotted using the same color.

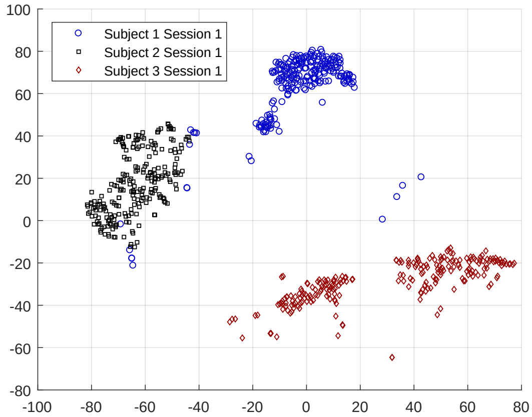
person appear close to each other, independent from the emotion elicited. This suggests that personality traits are of the factors that most influences PSD features from EEG signals, above others including the subject's affective state. Such result is against the construction of a subject-independent model that is valid for unseen users, and suggest that positive classification results obtained by some authors are more likely due to the class imbalance in the datasets used in their experiments than to the adequacy of the procedure for the problem at hand. For example, accuracy reported in (Katsigiannis and Ramzan 2017) is around 0.62 in valence and arousal, when using a SVM with a Radial Basis Function (RBF) kernel. However, the database was unbalanced (56%-44% in arousal and 61%-39% in valence).

Although the plots shown in Figures 1 and 2 clearly discourages the use of subject-independent modelling approaches, they also support the use of EEG signals for biometric authentication. However, one basic characteristic of suitable biometric authentication methods relate to permanence, i.e., the trait should be reasonably invariant over time with respect to the specific matching algorithm. One way to test permanence is using multiple session data. Figure 3 (a) shows an example of a 2-D data representation of three session for a single user in the SEED database. A strong dependency from the session can be observed in this plot, suggested by the clusters than can be easily distinguished. This indicates that there are aspects related to the session, such as the position of the electrodes, that have a considerable impact on the signal. This effect plays against the permanence property of EEG signals across multiple sessions and it is consistent with the relatively poor results obtained in very recent works when considering a multiple session scenario, e.g. (Arnau-González et al. 2018).

To compare the kind of variability that different sessions introduce in this kind of data, Figure 3 (b) displays the




(a)




(b)

Figure 3: Dimensionality reduction by t-SNE on (a) three different sessions for a same subject; and (b) three different subjects for a same session.

data from one of the sessions in (a) along with similar data from two other subjects using the same embedding. As it can be seen, both kinds of variability, across users and across sessions are roughly similar in terms of separability. Inspecting these two plots carefully, we can observe that this separability causes that samples from session 3 of subject 1 (see Figure 3 (a)) appear mixed with samples from session 1 of subject 3 (see Figure 3 (b)). Such an effect may potentially yield incorrect outputs in a biometric identification context when multiple sessions are considered.

## CONCLUSIONS

A visual exploratory analysis on several publicly available databases containing annotated EEG signals has been carried out. As a consequence, the extreme variable behavior of this kind of data has been put forward. The arguments provided in this paper are consistent with research results reported in recent literature, and are against the construction of a global model for emotion detection that is valid across the entire population. In addition, results reported in relation to the effect of the session suggest that even a personalized model per user may only be effective along the same session when data was captured, hence imposing a strong limitation on the practical applicability of PSD features from EEG signals for emotion detection. The same principles apply in the user identification case. The separability caused by the session is of a similar magnitude to that caused by the subject, and has a negative effect on the permanence property required in a biometric context.

In view of the results reported in this paper, managing the variability introduced when dealing with different subjects, sessions and equipment seems to be a very hard problem. While most previous research and experiments have been done considering one particular aspect, we suggest that their whole variability must be taken into account in order to significantly improve the performance results obtained to date. In particular, it seems feasible to use data related to the emotion, the session and the identity together, e.g. by designing specific mechanisms to reduce/cancel the subject-related and/or session-related component from the EEG signal, as recently proposed by Arevalillo-Herráez et al. (2019).

## ACKNOWLEDGMENTS

This research has been partly supported by CECOTEC INNOVACIONES, S.L. and the Spanish Ministry of Economy and Competitiveness through projects TIN2014-59641-C2-1-P and PGC2018-096463-B-I00.

## REFERENCES

Arevalillo-Herráez M.; Cobos M.; Roger S.; and García-Pineda M., 2019. *Combining Inter-Subject Modeling with a Subject-Based Data Transformation to Improve Affect Recognition from EEG Signals*. *Sensors*, 19, no. 13. ISSN 1424-8220. doi:10.3390/s19132999.

Arnau-González P.; Arevalillo-Herráez M.; Katsigiannis S.; and Ramzan N., 2018. *On the influence of affect in EEG-based subject identification*. *IEEE Transactions on Affective Computing*, 1–1. ISSN 1949-3045. doi:10.1109/TAFFC.2018.2877986.

Arnau-González P.; Arevalillo-Herráez M.; and Ramzan N., 2017. *Fusing highly dimensional energy and connectivity features to identify affective states from EEG signals*. *Neurocomputing*, 244, 81 – 89. ISSN 0925-2312. doi:http://dx.doi.org/10.1016/j.neucom.2017.03.027.

Ayesh A.; Arevalillo-Herráez M.; and Ferri F., 2014.

*Cognitive reasoning and inferences through psychologically based personalised modelling of emotions using associative classifiers.* In *IEEE 13th International Conference on Cognitive Informatics Cognitive Computing (ICCI*CC)*. 67–72. doi:10.1109/ICCI-CC.2014.6921443.

Ayesh A.; Arevalillo-Herráez M.; and Ferri F.J., 2016. *Towards Psychologically based Personalised Modelling of Emotions Using Associative Classifiers. International Journal of Cognitive Informatics and Natural Intelligence (IJCINI)*, 10, no. 2, 52–64. doi:10.4018/IJCINI.2016040103.

Duan R.N.; Zhu J.Y.; and Lu B.L., 2013. *Differential entropy feature for EEG-based emotion classification.* In *6th International IEEE/EMBS Conference on Neural Engineering (NER)*. IEEE, 81–84.

Hadjidimitriou S.; Charisis V.; and Hadjileontiadis L., 2015. *Towards a Practical Subject-Independent Affective State Recognition Based On Time-Domain EEG Feature Extraction. International Journal of Heritage in the Digital Era*, 4, no. 2, 165–178.

Katsigiannis S. and Ramzan N., 2017. *DREAMER: A Database for Emotion Recognition Through EEG and ECG Signals from Wireless Low-cost Off-the-Shelf Devices. IEEE Journal of Biomedical and Health Informatics.*

Koelstra S.; Muhl C.; Soleymani M.; Lee J.S.; Yazdani A.; Ebrahimi T.; Pun T.; Nijholt A.; and Patras I., 2012. *DEAP: A Database for Emotion Analysis ;Using Physiological Signals. Affective Computing, IEEE Transactions on*, 3, no. 1, 18–31. ISSN 1949-3045. doi:10.1109/T-AFFC.2011.15.

Liu S.; Zhang D.; Xu M.; Qi H.; He F.; Zhao X.; Zhou P.; Zhang L.; and Ming D., 2015. *Randomly dividing homologous samples leads to overinflated accuracies for emotion recognition. International journal of psychophysiology : official journal of the International Organization of Psychophysiology*, 96, no. 1, 2937. ISSN 0167-8760.

Liu Y.; Sourina O.; and Nguyen M.K., 2010. *Real-Time EEG-Based Human Emotion Recognition and Visualization.* In *International Conference on Cyberworlds (CW)*. 262–269. doi:10.1109/CW.2010.37.

Lu Y.; Zheng W.L.; Li B.; and Lu B.L., 2015. *Combining Eye Movements and EEG to Enhance Emotion Recognition.* In Q. Yang and M. Wooldridge (Eds.), *International Joint Conference on Artificial Intelligence (IJCAI)*. AAAI Press. ISBN 978-1-57735-738-4, 1170–1176.

Maaten L.v.d. and Hinton G., 2008. *Visualizing data using t-SNE. Journal of Machine Learning Research*, 9, no. Nov, 2579–2605.

Morris J.D., 1995. *Observations: SAM: the Self-Assessment Manikin; an efficient cross-cultural measurement of emotional response. Journal of Advertising Research*, 35, no. 6, 63–68.

Petrantonakis P. and Hadjileontiadis L., 2010. *Emotion Recognition From EEG Using Higher Order Crossings. IEEE Transactions on Information Technology in Biomedicine*, 14, no. 2, 186–197. ISSN 1089-7771. doi:10.1109/TITB.2009.2034649.

Russell J.A., 1979. *Affective Space is Bipolar. Journal of Personality and Social Psychology*, 37, no. 3, 345.

Salmeron-Majadas S.; Arevalillo-Herráez M.; Santos O.C.; Saneiro M.; Cabestrero R.; Quirós P.; Arnau D.; and Boticario J.G., 2015. *Artificial Intelligence in Education: 17th International Conference, AIED 2015, Madrid, Spain, June 22-26, 2015. Proceedings*, Springer International Publishing, Cham, chap. Filtering of Spontaneous and Low Intensity Emotions in Educational Contexts. ISBN 978-3-319-19773-9, 429–438.

Sohaib A.T.; Qureshi S.; Hagelbäck J.; Hilborn O.; and Jerčić P., 2013. *Foundations of Augmented Cognition: 7th International Conference, AC 2013, Held as Part of HCI International 2013, Las Vegas, NV, USA, July 21-26, 2013. Proceedings*, Springer Berlin Heidelberg, Berlin, Heidelberg, chap. Evaluating Classifiers for Emotion Recognition Using EEG. ISBN 978-3-642-39454-6, 492–501.

Soleymani M.; Asghari-Esfeden S.; Pantic M.; and Fu Y., 2014. *Continuous emotion detection using EEG signals and facial expressions.* In *IEEE International Conference on Multimedia and Expo (ICME), 2014*. 1–6. doi:10.1109/ICME.2014.6890301.

Soleymani M.; Lichtenauer J.; Pun T.; and Pantic M., 2012a. *A Multimodal Database for Affect Recognition and Implicit Tagging. IEEE Transactions on Affective Computing*, 3, no. 1, 42–55. ISSN 1949-3045. doi:10.1109/T-AFFC.2011.25.

Soleymani M.; Lichtenauer J.; Pun T.; and Pantic M., 2012b. *A multimodal database for affect recognition and implicit tagging. Affective Computing, IEEE Transactions on*, 3, no. 1, 42–55.

Wang X.W.; Nie D.; and Lu B.L., 2014. *Emotional state classification from EEG data using machine learning approach. Neurocomputing*, 129, 94–106.

Zheng W.L. and Lu B.L., 2015. *Investigating Critical Frequency Bands and Channels for EEG-based Emotion Recognition with Deep Neural Networks. IEEE Transactions on Autonomous Mental Development*, 7, no. 3, 162–175. doi:10.1109/TAMD.2015.2431497.